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14. ABSTRACT

Periodically, the US Army conducts detailed measurement surveys of its soldiers as a way to understand the impact that changes in soldier body size have for the design, fit and sizing of virtually every piece of clothing and equipment that Soldiers wear and use in combat. Recently finished US Army Anthropometric Survey (ANSUR II) has collected 3D body scan data of soldiers at the Natick Solider Center (NSC), as shown in Figure 1. By applying new techniques for shape analysis and classification to these 3D body scan data will help designers of clothing and

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Report Title

Final Report for Manifold Learning for 3D Shape Description and Classification

ABSTRACT

Periodically, the US Army conducts detailed measurement surveys of its soldiers as a way to understand the impact that changes in soldier body size have for the design, fit and sizing of virtually every piece of clothing and equipment that Soldiers wear and use in combat. Recently finished US Army Anthropometric Survey (ANSUR II) has collected 3D body scan data of soldiers at the Natick Solider Center (NSC), as shown in Figure 1. By applying new techniques for shape analysis and classification to these 3D body scan data will help designers of clothing and personal protection equipment to understand and fit Army population. The overall research goal of this proposal is to create a new manifold learning framework for large-scale graph decomposition and approximation problems by low-rank approximation and guarantee computable, stable and fast optimizations for 3D shape description and classification. The PI's group has published (or accepted for publication) 1 book through Springer and 13 scientific papers partially supported by this grant. In particular, these papers are in top journals and conference proceedings such as TPAMI, IJCV, TCSVT, ICCV, AAAI, SDM, ACM MM, etc. One paper, 1 out of 384, receives the Best Paper Award in SDM 2014. The PI, Dr. Y. Raymond Fu has received the 2014 INNS Young Investigator Award, from International Neural Networks Society (INNS), 2014. Leveraged by this grant, the PI has been granted an ARO Young Investigator Program (YIP) Award and a Defense University Research Instrumentation Program (DURIP) award.

Enter List of papers submitted or published that acknowledge ARO support from the start of the project to the date of this printing. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Received		Paper
06/04/2014	2.00	Kang Li, Yun Fu. Prediction of Human Activity by Discovering Temporal Sequence Patterns, IEEE Transactions on Pattern Analysis and Machine Intelligence, (01 2014): 0. doi: 10.1109/TPAMI.2013.2297321
06/04/2014	3.00	Ming Shao, Dmitry Kit, Yun Fu. Generalized Transfer Subspace Learning Through Low-Rank Constraint, International Journal of Computer Vision, (08 2014): 0. doi: 10.1007/s11263-014-0696-6
06/04/2014	4.00	Liangyue Li, Sheng Li, Yun Fu. Learning low-rank and discriminative dictionary for image classification, Image and Vision Computing, (03 2014): 0. doi: 10.1016/j.imavis.2014.02.007
06/04/2014	10.00	Ya Su, Sheng Li, Shengjin Wang, Yun Fu. Submanifold Decomposition, IEEE Transactions on Circuits and Systems for Video Technology, (06 2014): 0. doi:
06/04/2014	11.00	Yuan Yao, Yun Fu. Contour Model Based Hand-Gesture Recognition Using Kinect Sensor, Circuits and Systems for Video Technology, IEEE Transactions on , (01 2014): 0. doi:

TOTAL: 5

Number of Papers published in peer-reviewed journals:

(b) Papers published in non-peer-reviewed journals (N/A for none)

Received Paper

TOTAL:

Number of Papers published in non peer-reviewed journals:

(c) Presentations

Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received Paper

TOTAL:

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Received		Paper
06/04/2014	5.00	Sheng Li, Yun Fu. Robust Subspace Discovery through Supervised Low-Rank Constraints, 2014 SIAM International Conference on Data Mining. 26-APR-14, . Philadelphia, PA: Society for Industrial and Applied Mathematics, Society for Industrial and Applied Mathematics
06/04/2014	6.00	Sheng Li, Peng Li, Yun Fu. Understanding 3D human torso shape via manifold clustering, SPIE Defense, Security, and Sensing. 29-APR-13, Baltimore, Maryland, USA. : ,
06/04/2014	7.00	Xu Zhao, Yuncai Liu, Yun Fu. Exploring discriminative pose sub-patterns for effective action classification, 21st ACM international conference on Multimedia. 21-OCT-13, Barcelona, Spain. : ,
06/04/2014	8.00	Ming Shao, Liangyue Li, Yun Fu. What Do You Do? Occupation Recognition in a Photo via Social Context, 2013 IEEE International Conference on Computer Vision (ICCV). 01-DEC-13, Sydney, Australia. : ,
06/04/2014	9.00	Yizhe Zhang, Ming Shao, Edward K. Wong, Yun Fu. Random Faces Guided Sparse Many-to-One Encoder for Pose-Invariant Face Recognition, 2013 IEEE International Conference on Computer Vision (ICCV). 01-DEC-13, Sydney, Australia. : ,
06/04/2014	12.00	Sheng Li, Ming Shao, Yun Fu. Locality Linear Fitting One-class SVM with Low-Rank Constraints for Outlier Detection, International Joint Conference on Neural Networks (IJCNN). 06-JUL-14, . : ,
06/04/2014	13.00	Shuyang Wang, Jinzheng Sha, Huaiyu Wu, Yun Fu. Hierarchical Facial Expression Animation by Motion Capture Data, IEEE International Conference on Multimedia and Expo . 14-JUL-14, . : ,
06/04/2014	14.00	Chengcheng Jia, Guoqiang Zhong, Yun Fu. Low-Rank Tensor Learning with Discriminant Analysis forAction Classification and Image Recovery, Twenty-Eighth AAAI Conference on Artificial Intelligence. 28-JUL-14, . : ,

TOTAL: **8**

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts):

(d) Manuscripts

Received Paper

TOTAL:

Number of Manuscripts:

Books

Received		Book
06/03/2014	1.00	Yun Fu, Yunqian Ma. Graph Embedding for Pattern Analysis, New York: Springer, (12 2013)
TOTAL:		**1**

Received	Book Chapter
TOTAL:	

Patents Submitted

Patents Awarded

Awards

-ONR Young Investigator Award
Office of Naval Research (ONR), 2014

-ARO Young Investigator Award
Army Research Office (ARO), 2014

-INNS Young Investigator Award
International Neural Networks Society (INNS), 2014

-SDM Best Paper Award
SIAM International Conference on Data Mining (SDM) Best Paper Award, 2014

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Chengcheng Jia	1.00	
Shuyang Wang	1.00	
FTE Equivalent:	**2.00**	
Total Number:	**2**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Yun Fu	0.10	
FTE Equivalent:	**0.10**	
Total Number:	**1**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

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The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

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Names of Personnel receiving masters degrees

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Total Number:

Names of personnel receiving PHDs

NAME
Total Number:

Names of other research staff

NAME	PERCENT_SUPPORTED
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Sub Contractors (DD882)

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Scientific Progress

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REPLY TO
ATTENTION OF

Final Report: Scientific Progress and Accomplishments

Title: Manifold Learning for 3D Shape Description and Classification
Proposal No: 63747-CS-II
Grant No: U. S. Army Research Office STIR under W911NF-13-1-0160
PI: **Yun Raymond Fu**, Assistant Professor, Northeastern University, Boston

1. Statement of the Problem Studied

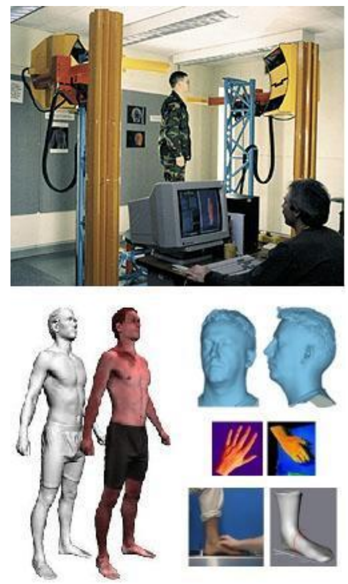

Figure 1: 3D Human Scan.

Periodically, the US Army conducts detailed measurement surveys of its soldiers as a way to understand the impact that changes in soldier body size have for the design, fit and sizing of virtually every piece of clothing and equipment that Soldiers wear and use in combat. Recently finished US Army Anthropometric Survey (ANSUR II) has collected 3D body scan data of soldiers at the Natick Solider Center (NSC), as shown in Figure 1. By applying new techniques for shape analysis and classification to these 3D body scan data will help designers of clothing and personal protection equipment to understand and fit Army population. *The overall research goal of this proposal is to create a new manifold learning framework for large-scale graph decomposition and approximation problems by low-rank approximation and guarantee computable, stable and fast optimizations for 3D shape description and classification*.

Traditional body shape description is based on a few anthropometric measurements, mostly chest, waist and hip circumferences. These simple measurements cannot completely capture three-dimensional shape variation of the human body. Current progress in 3D scanning technology made capture of 3D shape of human body possible. Although researches have been conducted in shape description and retrieval of the human body, there is no report in successful 3D shape classification direction. It is believed the classification is important because it will benefit design of garment, sportswear, personal protection clothing and equipment, office and health care device, etc. Therefore it is desirable to develop an effective shape descriptor and robust shape classification method for 3D human body surface data. Moreover, large scale (big) 3D shape data, such as the ANSUR II, may cause intractable computational complexity, especially for graph decomposition based machine learning methods, *e.g.* manifold learning, graph embedding, subspace learning, clustering.

2. Scientific Accomplishments

The PI's group has published (or accepted for publication) 1 book through Springer and 13 scientific papers partially supported by this grant. In particular, these papers are in top journals and conference proceedings such as TPAMI, IJCV, TCSVT, ICCV, AAAI, SDM, ACM MM, etc. One paper, 1 out of 384, receives the **Best Paper Award** in SDM 2014. The PI, Dr. Y. Raymond Fu has received the **2014 INNS Young Investigator Award**, from International Neural Networks Society (INNS), 2014. Leveraged by this grant, the PI has been granted an **ARO Young Investigator** Program (YIP) **Award** with a title of "Intention Sensing through Video-based Imminent Activity Prediction", and a **Defense University Research Instrumentation Program (DURIP) award** with a title of "3D Data Acquisition Platform for Human Activity Understanding".

3. Summary of Results

Discovering the variations in human torso shape plays a key role in many design-oriented applications, such as suit designing. With recent advances in 3D surface imaging technologies, people can obtain 3D human torso data that provide more information than traditional measurements. However, how to find different human shapes from 3D torso data is still an open problem. From this STIR project, we have created a new algorithmic tool set of modeling large-scale high dimensional data [1-14]. For uncertainty visual representation, we proposed a class of manifold and subspace learning methods [1] including submanifold decomposition [4], manifold clustering [11], deep learning [14], one-class classification [10], low-rank and discriminative dictionary learning [6], robust low-rank subspace discovery [7], low-rank tensor completion [8] and low-rank transfer subspace learning [3]. We also proposed applications of these techniques to analyzing spatial-temporal patterns of human motion, action, and activity [2], 3D hand-gesture recognition [5], expression animation by motion capture [9], 3D human torso shape understanding [11], discriminative pose sub-patterns [12], human gesture in social context [13]. This report will highlight the details in [4, 7, 8, 11].

3.1 Manifold Modeling

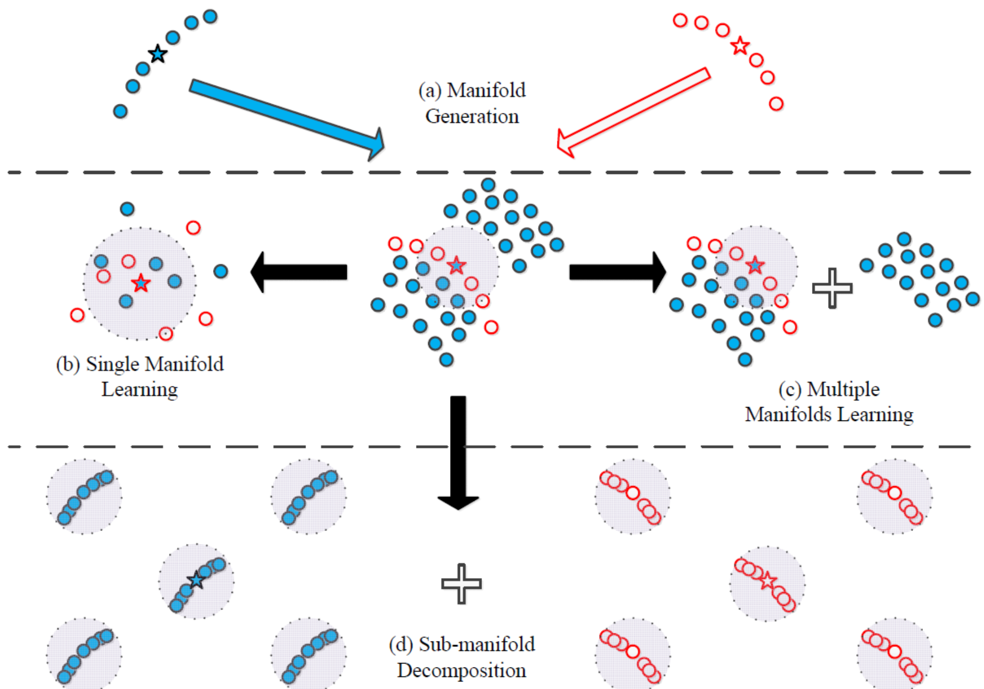

Figure 2: Toy example for submanifold decomposition. (a) The original data on the top are fused by two uncorrelated manifolds, blue and red respectively. Any point (denoted by star) is affected by and belongs to both of the two manifolds. (b) Traditional manifold learning algorithms can only extract a manifold based on nearest neighborhood relationship. (c) Multiple manifold learning algorithms learn two manifolds that are separated in distance, and assume any point can only subject to one manifold. (d) SMD learns two manifolds simultaneously.

Low-dimensional structures embedded in high dimensional data space can be extracted by spectral analysis and manifold learning. Standard approaches for manifold learning are usually based on the assumption that there is a dominant low-dimensional manifold, while other variations are considered with minor priority. We instead consider the scenario that a pair of distinct manifolds intertwined in the same high-dimensional space which can be decomposed for analysis. The novel submanifold decomposition (SMD) algorithm, shown in Figure 2, has three contributions: 1) A submanifold framework is proposed to model the high-dimension dataset which is dominated by more than one factor; 2) A nonlinear manifold decomposition method is presented to extract two intertwined manifolds from a dataset in a discriminative manner, and 3) In order to solve the "Out-of-Sample" problem of nonlinear SMD, a linear extension of SMD is developed which is effective to extract two linear submanifolds. We demonstrated that comparing with existing manifold learning methods that only extract one dominant manifold, the proposed SMD and its linear extension are capable of extracting a pair of submanifolds discriminatively and effectively. Moreover, the two extracted manifolds can complement each other to enhance the representation performance.

Articulated configuration of human body parts is an essential representation of human shape and motion, therefore is well suited for classifying. We proposed a novel approach to exploring the discriminative pose sub-patterns based on the submanifold decomposition assumption. These pose sub-patterns are extracted from a predefined set of 3D poses represented by hierarchical motion angles. The basic idea is motivated by the two observations: (1) There exist representative sub-patterns in each action class, from which the action class can be easily differentiated. (2) These sub-patterns frequently appear in the action class. By constructing a connection between frequent sub-patterns and the discriminative measure, we developed the Support Sub-Pattern Induced learning algorithm for simultaneous feature selection and feature learning. The generalization capability of this new model is inductive enough to extend the application to ARMY video data.

3.2 Low-Rank Manifold Modeling

Subspace learning can facilitate manifold modeling for feature extraction and classification. However, its performance would be heavily degraded when data are corrupted by large amounts of noise. Inspired by recent work in matrix recovery, we tackle this problem by exploiting a subspace that is robust to noise and large variability for manifold modeling. Specifically, we propose a novel Supervised Regularization based Robust Subspace (SRRS) approach via low-rank learning, shown in Figure 3. Unlike existing subspace methods, our approach jointly learns low-rank representations and a robust subspace from noisy observations. At the same time, to improve the classification performance, class label information is incorporated as supervised regularization. The problem can then be formulated as a constrained rank minimization objective function, which can be effectively solved by the inexact augmented Lagrange multiplier (ALM) algorithm. Our approach differs from current sparse representation and low-rank learning methods in that it explicitly learns a low-dimensional subspace where the supervised information is incorporated.

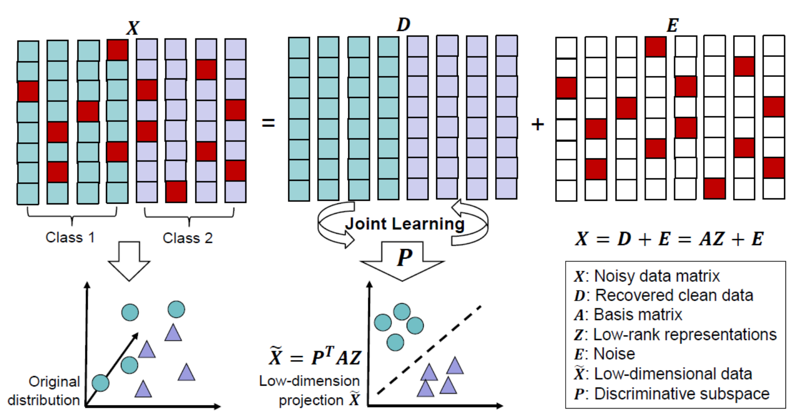

Figure 3: Robust low-rank subspace recovery. We jointly remove noise from data X and learn robust subspace P. The corrupted samples are mixed in the original space, but they are well separated in the learned subspace.

3.3 Low-Rank Tensor Manifold Modeling

Tensor completion can further facilitate low-rank manifold modeling for extraction of the intrinsic structure of the multimode data. We present a supervised low-rank tensor completion method for dimensionality reduction, to learn an optimal subspace for manifold modeling. Our model automatically learns the low dimensionality of tensor, opposed to manually pre-defined, as other dimensional reduction methods. Considering the underlying structure information of the whole high-dimensional dataset, it can use the low-rank learning to extract the structure for image recovery, while integrating with the discriminant analysis criterion. Figure 4 shows the framework of our method applied to the video-based action classification. We first select a training set from an action video database to learn the low-rank projection matrices, which are then used to calculate a tensor subspace for the action classification. When calculating the low-rank projection matrices, we adopt a discriminant analysis criterion as a regularizer to avoid over-fitting. Meanwhile, with this discriminant analysis criterion, supervisory information is seamlessly integrated in the low-rank tensor completion model. After projecting the original training and testing sets to the learned tensor subspace, we predict the labels of the test video sequences with a K-nearest neighbor (KNN) classifier. We add the sample information to recovery some face images by removing different illuminations. The contributions of this work are 1) a new discriminative method for low-rank tensor completion, which automatically learns the low dimensionality of the tensor subspace for feature extraction; 2) integration of the discriminant analysis criterion in the low-rank tensor completion model based on the given supervisory information; 3) extraction of the underlying structure of the original tensor data by low-rank learning, which reconstructs the data from the learned tensor subspace, for high-dimensional image recovery.

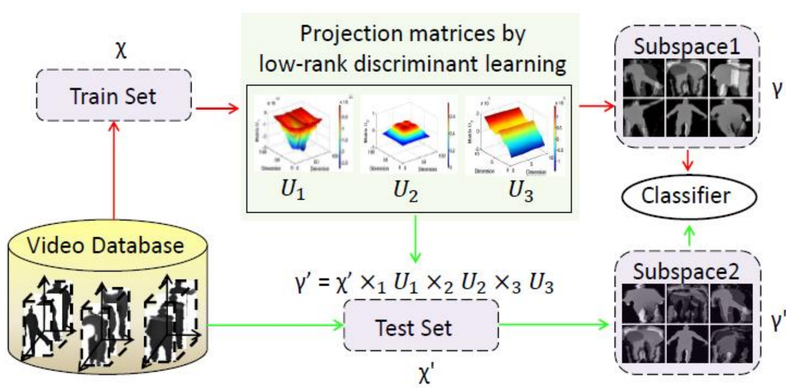

Figure 4: Low-rank tensor manifold modeling. The tensor training set X is used for calculating the low-rank projection matrices, which are employed for subspace alignment of training and testing set Y and Y'.

3.4 Dataset

The Civilian American and European Surface Anthropometry Resource (CAESAR) database, Figure 5, contains 3D scans, seventy-three anthropometry landmarks, and traditional measurements data of 5000 subjects. In our experiments, we select the torso data of 1,100 subjects (about 650 male and 450 female) from CAESAR database. For simplicity, we only choose the standing pose of every subject, and convert the scanned data of each subject into a column vector before evaluating different clustering algorithms.

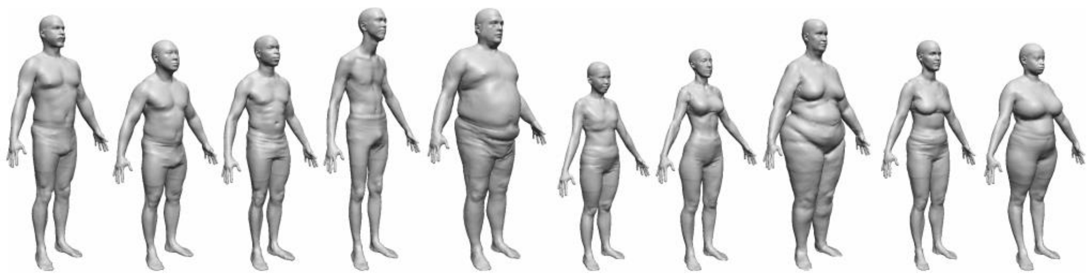

Figure 5: Image Source: http://grail.cs.washington.edu/projects/digital-human/pub/allen03space.pdf

The MSR hand gesture 3D database (Oreifej, Liu, and Redmond 2013; Wang et al. 2012) contains 12 classes of hand gestures: letter “Z”, “J”, “Where”, “Store”, ‘Pig”, “Past”, “Hungary”, “Green”, “Finish”, “Blue”, “Bathroom”, and “Milk”. These are performed by 10 subjects, with each subject performs 2-3 times. There are total of 333 samples, each is an action video consisting of a depth image sequence. We use the same experimental set-up as (Oreifej, Liu, and Redmond 2013) (Wang et al. 2012) in this experiment. All the subjects are independent, and each video sequence is subsampled to be the size of 80x80x18. The image dimension is sufficient to represent the gesture, and the third dimension is due to the least number of the video sequence.

The MSR action 3D database contains 20 classes of actions. This includes “arm waving”, “horizontal waving”, “hammer”, “hand catching”, “punching”, “throwing”, “drawing x”, “drawing circle”, “clapping”, “two hands waving”, “sideboxing”, “bending”, “forward kicking,” “side kicking”, “jogging”, “tennis swing,” “golf swing,” “picking up and throwing”. Each action is performed by 10 subjects, each performing 2-3 times. There are 567 samples in total. The action video is represented as a high-dimensional tensor in this experiment. In the following, we report two sets of results performed under different experimental settings.

3.5 Evaluation Results

In the evaluation, we propose to use spectral clustering approach on torso manifold for analyzing the shape variations in 3D human torso data. In particular, the high-dimensional torso data are first represented in a low-dimensional space that is learnt by manifold embedding algorithms such as LLE and LE. Then we perform spectral clustering on the manifold to group the torso data points into several disjoint subsets. We evaluate the performance of our algorithm on the CAESAR 3D human torso database. Experimental results show that our approach achieves better performance than the compared clustering method, and the cluster centers discovered by our approach can describe the discrepancies in both genders and human shapes.

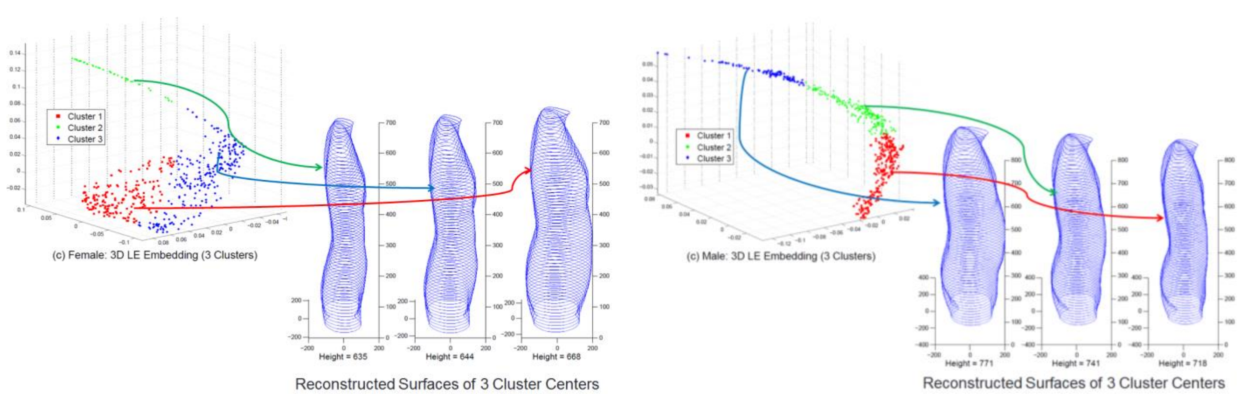

Figure 6: Visualization of 3-cluster manifold clustering results on male (right) and female torsos (left).

We testify our algorithm on both male and female torsos. The traditional K-Means algorithm on the PCA embedding space is chosen as our baseline. We observed that the data distribution discovered by PCA is not smooth, and some data points can be easily regarded as outliers, which often lead to negative effects on clustering. Therefore, the boundaries of different clusters are unclear, and there is even an obvious overlap between clusters. As a result, it is difficult to analyze torso shape variations based on the clustering results.

Figure 6 show the spectral clustering results after LE embedding, respectively. They demonstrate that: (1) manifold learning algorithms, such as LLE and LE, could reveal the underlying structure of 3D female torsos. We can observe that the manifold is smooth, and there are few outliers. (2) our clustering algorithm successfully groups the data into several clusters, and there is almost no overlap between different clusters. We can obtain several disjoint clusters using our proposed algorithm. How to analyze the shape variations according to the clustering results? A rational strategy is to use the center of cluster as the prototype for each cluster. To visualize different cluster centers, we reconstruct the torso surfaces according to the original 3D torso data, and illustrate 3 cluster centers in Figure 6. We also show the average heights of each cluster. It's interesting that 3 cluster centers display significant differences in their bust girth and height, and their sizes are increased gently. In other words, we are able to discover the shape variations among a large group of torsos when given a proper number of clusters (i.e., the number of shape types).

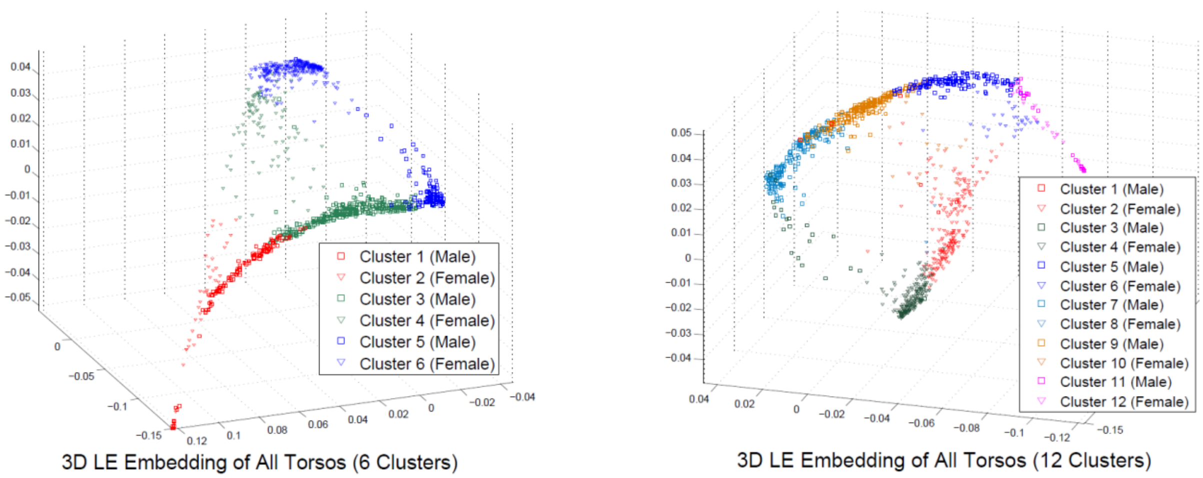

Figure 7: Visualization of clustering results on all torsos (6 Clusters)

Another interesting question is that can we discover the shape variations without the gender information. We evaluate the performance of our algorithm on all the torsos. Figure 7 shows the clustering results of all torsos after manifold embedding when the numbers of clusters are 6 and 12. We can observe from Figure 7 that male data and female data lie in two different manifold structures. When the number of clusters comes to 12, our algorithm can distinguish both gender and shape types.

Table 1-3 show the accuracy of different methods on the MSR 3D databases. It should be evident that, the proposed method performs better than the state-of-the-art low-rank tensor representation learning methods. HON4D+D_{disc} (Oreifej, Liu, and Redmond 2013) is the latest work on the gesture database using normal orientation histogram. Zhang et al.'s work (Zhang et al. 2013) proposed to rectify align images with distortion and partial missing, which used image sequence after low-rank learning in this experiment. It had lower accuracy than our method, as it relies on the original images and can deal with the trivial changing, such as sparse noise, small fragment, and distortion; while it is not suitable for the large scale of movement, distortion or rotation in the gesture classification task. Zhong and Cheriet's method is less effective when compared with ours. In the Test One and Cross Subject sets our method performs best. In the Test Two set, we have an accuracy just 2% lower than Chen et al.'s method. For Zhang et al's (Zhang et al. 2013) work, we used entire images in the database, i.e., 10 x 567 = 5670 images. Still, it was able to deal with the trivial sparse noise or distortion, such as the digit '3' in their test experiment (Zhang et al. 2013). However, the action video containing large scale movements in the arms or legs, making it not suitable for this application.

Method	Accuracy %
HON4D $+D_{disc}$	92.45
HON4D	87.29
Zhang et al.	89.93
Zhong et al.	69.44
LRTD	**99.09**

Table 1: Results for the MSR gesture database.

Method	Accuracy %
HON4D $+D_{disc}$	88.89
HON4D	85.85
Zhang et al.	95.96
Zhong et al.	92.88
LRTD	**98.50**

Table 2: Results for the MSR action database.

Table 3: Accuracy (%) of 3 sets on the MSR action database.

		Chen	Zhang	Zhong	Ours
Test One	AS1	97.3	46.67	92.76	**99.34**
	AS2	96.1	47.71	98.08	**99.36**
	AS3	98.7	11.33	80.26	**99.34**
	Average	97.4	35.24	90.37	**99.35**
Test Two	AS1	98.6	45.95	77.63	**98.68**
	AS2	**98.7**	47.24	91.03	97.44
	AS3	**100**	10.81	90.79	96.05
	Average	**99.1**	34.67	86.48	97.39
Cross Subject Test	AS1	96.2	44.35	91.67	**98.33**
	AS2	83.2	46.16	85.83	**97.50**
	AS3	92.0	10.81	85.83	**99.17**
	Average	90.5	33.78	87.78	**98.33**

3.6 Conclusion

From the above experimental results, we can conclude that the proposed clustering algorithm could automatically discover different shape types. First, we show on both female and male torsos that manifold embedding algorithms can reveal the underlying structures of high-dimensional torso data. Second, compared with the baseline method, K-Means, our algorithm clearly groups the torsos into several disjoint subsets. In addition, if the gender information is unknown, our algorithm can also distinguish both gender and shape types by virtue of manifold clustering. An open question is how to design a strategy to determine the optimal number of clusters, which could be considered in our future work. Results on the MSR hand gesture 3D database and the MSR action 3D database have shown that our method performs better than the state-of-the-art low-rank tensor representation learning methods.

4. Scientific Significance

By investigating novel low-rank matrix approximation methodologies in a new manifold learning framework coupled with graph embedding and subspace learning, the proposed research seeks to advance basic understanding and visual representation of large-scale 3D scan data, and will allow for important advances in fundamental computer vision and pattern classification research. Such low-rank graph approximation by divide-approximate-combine and graph-based locality preserving hashing for enhancing the computability of large-scale tasks would be a significant contribution, which will guarantee computable, stable and fast optimizations. This project will be a collaborative research with the Natick Soldier Research, Development and Engineering Center (NSRDEC), which may significantly facilitate and advance the ongoing US Army Anthropometric Survey. Such progresses will significantly advance the visual intelligence field and contribute to the accomplishment of the Army's mission.

5. Future Research Plans

The project starts by building databases from the collaborators in NSC; then comprehensively investigates the proposed new methodologies; finally validates the 3D body shape clustering applications. It is strongly believed that the theoretical contribution of this research may pave the foundation for novel techniques in solving important problems of visual understanding and large-scale visual analytics. Such research endeavor is sustainable and can go well beyond the 9-month scope, which is the PI's long-term career goal. The leveraged ARO YIP award and DURIP award are concrete examples of future research plan within the PI’s key research interests.

6. Bibliography

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